Determinants and Consequences of Herding in P2P Lending Markets

Research-in-Progress

Martina Greiner
University of Nebraska at Omaha
mgreiner@unomaha.edu

ABSTRACT

In this paper, we are interested in the factors that influence herding behavior in P2P lending marketplaces. We are using data from Prosper.com to examine whether internal market specific factors and external economic factors influence the amount of herding exhibited in the market. We also investigate what consequences herding has and how marketplace participants can benefit or suffer from herding behavior in the marketplace. Based on previous models of herding in P2P lending, we calculate a herding measure over time. This herding measure is the basis for our analyses. Our preliminary analyses show support that internal factors measuring uncertainty, lenders experience, and search costs in the market influence herding. We receive inconclusive results for external factors measuring uncertainty, volatility, and bullishness in the marketplace's economic environment. Herding has several implications for borrowers and lenders including potentially lower interest rates for borrowers but fewer completed listings.

Keywords

Microloan Markets, P2P Lending Market, Herding, Time Series

INTRODUCTION

P2P lending markets allow their customers to loan money to each other. Customers who desire money (borrowers) post loan requests outlining their need for a loan alongside a proposed interest rate and other information about themselves. Customers who want to invest money (lenders) bid on these loan listings and once enough funds are reached, a loan is created. In auction model marketplaces, borrowers can also choose to continue the auction and wait for lenders to bid down their proposed interest rate. The marketplace owner facilitates the whole process of loan request, bidding, loan creation, and loan serving. Prosper, the first P2P lending market in the US, opened 2006. Since then other markets in and outside the US have launched.

In this paper, we will focus on Prosper to study a special decision making behavior of lenders called herding. Lenders have to decide in which loans to invest. Loans are not backed by securities and lenders have to choose their loans carefully and assess the likelihood whether a borrower will pay back a loan. One way to choose listings is to evaluate information provided on the loan listing. Another way is to observe on what loans other lenders are bidding. Observing and imitating the bidding behavior of other lenders is called herding. Commonly, herding behavior is explained with informational cascades. Informational cascades take place "when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information" (Bikhchandani et al. (1992), page 994). Herding is likely to be relevant in P2P lending marketplaces. Due to their young age, there is still uncertainty surrounding the optimal lending decision and which listings offer the best return and least likelihood of default. In addition, the number of listings that a lender needs to evaluate is high, resulting in high search costs and a long decision process if lenders diligently evaluate a borrower. In addition, it is fairly easy to observe what others are doing in marketplaces. Bidding history in P2P lending marketplaces are commonly available and often prominently displayed. All this sets up P2P lending marketplaces for herding.

Why is it important to study herding in P2P lending marketplaces? P2P lending marketplaces differ from other electronic C2C markets that they need some coordinated action on the lenders' side. A listing is funded only if it can attract enough lenders. We can think of this model as a "multi-winner" auction (Wang et al. 2010). If absolutely no herding behavior takes place, bids would be widely dispersed among listings. Only few listings would get enough funding, and the majority of the money would be bound in listings that never fund – wasting valuable resources of lenders (Herzenstein et al. 2011; Wang et al. 2010). So, some herding behavior is beneficial for lenders as well as the marketplace. But borrowers may benefit as well. In auction-model P2P lending marketplaces, lenders' concerted bidding behaviors could lead to some listings receiving many bids, potentially lowering the interest rate that the borrower receives.

Studies in P2P lending research show that herding is occurring in P2P lending markets. In this paper, we are contributing to this area of research by looking at determinants of herding behavior and empirically testing them. To our knowledge, this is the first study in P2P lending that evaluates herding behavior over time and looks at determinants and consequences of herding behavior with the help of time series. Evaluating herding behavior helps to better understand the decision making behavior of lenders and improve P2P marketplace practices.

HERDING IN P2P LENDING MARKETS

Herding in P2P lending has been investigated in different ways. Common to all studies is the conclusion that some degree of herding is going on. Most interesting to us is how the authors measure herding. So far, there is no agreement on how to measure herding. And this is not surprising. Studying herding behavior is difficult, since in most social and economic situation, the researcher does not know what kind of private information a decision maker has and whether the outcome is due to imitating others or result of their own cognitive processes. The following figure gives a summary of P2P lending studies that investigate herding and how they define and measure herding.

Study	Summary of results	Manifestation of herding	Measurement of herding
Herzenstein et al. (2011)	Evidence of strategic herding. More herding before listing is fully funded, less herding afterwards.	"Likelihood of bidding on an auction with more bids".	Logit regression (data point = each bid) DV = Another bid Y/N IV (herding measure) = Natural log of number of bids
Ceyhan et al. (2011)	Evidence of herding.	"A lenders' belief that the listing will succeed [.] is based on the number of bids that have been accumulated […] from the beginning to time *t*"	Simulation. Also looks at the shape of bids over the time of the auction (similar to Krumme and Herrero (2009))
Zhang and Liu (2012)	Evidence of irrational and rational herding.	Amount lent is "ultimate measure of how a listing is received by a lender".	Multiple regression (data point (each day of a listing) DV = Amount bid on auction day t IV (herding measure) = Sum Amount bid at t-1
Luo and Lin (2013)	Evidence of herding. Herding increases with more bids and friend bids.	A lenders' decision-making time variation.	Herding is measured as the average time interval between two consecutive bids. Smaller time intervals are evidence for herding.
Lee and Lee (2012)	Evidence of herding and diminishing marginal effect as bidding advances.	Likelihood of being fully funded based on the current level of participation (percentage funded so far)	Multinomial logit market-share model DV = Daily markets share bidders or [bid money] (number of bidders [or bid amount] of auction day *t* divided by cumulated number of bidders [or bid amount] at auction day *t*) of auction day *t* IV (herding measure) = participation rate = percentage funded previous day *t -1*
Krumme and Herrero (2009)	Evidence of herding.	"The rate at which bids are accrued to listings".	Development of percentage funded over the auction time.

Table 1: Overview P2P Herding Literature about Measuring Herding

RESEARCH MODEL – HYPOTHESES

A major assumption of herding is that uncertainty gives rise to herding. In the following we are looking at two main sources of uncertainty – marketplace specific factors that focus on characteristics of a specific marketplace and general economic factors that focus on the overall climate of the economy. The determinants are novel contributions, rooted in previous research but limited by available data.

Marketplace Specific Determinants

In this section, we look at how marketplace specific factors influence the amount of herding. In general, P2P lending markets are characterized by high uncertainty mainly due to information asymmetries (Greiner et al. 2009; Herzenstein et al. 2011). A lender does not know a prior whether a borrower is trustworthy and whether the borrower will pay back the loan. A lender can use several factors such as economic or social characteristics of the listing and borrower to infer on the borrower's trustworthiness (Greiner et al. 2010), however, this is a difficult process. Previous bidding behavior from others could serve as a proxy for trustworthiness, as other lenders have deemed that borrower trustworthy enough to borrow money to (Zhang et al. 2012). A lender who carefully evaluates a borrower incurs search costs. Herding behavior has been associated with search costs (LIn et al. 2010). We expect in this environment with uncertain returns and high search costs, that when a lender has to choose from many listings, that the search process becomes more complex and that the lender is not able to diligently evaluate listing specific factors (e.g., credit grade, Q&A, soft factors). This makes following actions from other lenders a practical approach. We also expect the herding measure to increase, the more lenders are active in the marketplace, b/c more lenders will follow other lenders' actions. As lenders become more familiar with the marketplace, the lending decisions, the more we expect that the influence of other lender's actions on their own actions will decrease, leading to lower herding. Uncertainty might also arise in an environment where many high risk listings are available (Zhang et al. 2012).

H1: The number of active listings positively influences herding.

H2: The number of active lenders positively influences herding.

H3: The experience of lenders negatively influences herding.

H4: The percentage of high risk active listings positively influences herding.

Marketplace's Environment Specific Determinants

Lenders do not act in a vacuum. They are likely to be influenced by factors outside the marketplace as well. Namely, the overall climate of the economy. Previous research suggests that decision makers in stock markets are more likely to herd in unstable compared to stable markets (Schachter et al. 1985). We expect that in high uncertain (e.g., reflected in the unemployment rate, inflation rate), volatile (e.g., reflected in Vix), and negative (e.g., reflect in SP500 and its change) climates, lenders are more likely to follow others as they are insecure in their own decisions and private information. This leads to the following hypothesis.

H5: A high volatile, uncertain, and negative economic climate positively influences herding.

Consequences of Herding

Herding could lead to several consequences for marketplace participants. In this paper, we look at three different outcomes from the borrower perspective. First, we expect that herding leads to a higher concentration on fewer listings with the consequences, that overall fewer listings will close compared to less herding. Also, with more bids for few listings, we can expect that we see an influence on how much the starting interest rate is bidden down (Wang et al. 2010). In addition, we expect the average interest rate to be lower than in periods of less herding. This leads to the following hypotheses:

H6: Herding positively influences bidding down the interest rate.

H7: Herding negatively influences the percentage of listings that are completed.

H8: Herding negatively influences the average interest rate.

DATA ANALYSIS

Calculating the Time Series for the Herding Measure

Regression Model for Calculating Herding Measure

The first step in measuring herding is to determine how to calculate the herding measure. Summarizing Table 1 above, we have four general possibilities of measuring herding in P2P lending marketplaces:

(1) Amount of bidding based on the previous amount bidden (Lee et al. 2012; Zhang et al. 2012).

(2) Likelihood of biding based on the number of previous bids (Herzenstein et al. 2011)

(3) Assessing the shape of the bidding rate over the time of the auction. A certain shape would suggest more or less herding (Ceyhan et al. 2011; Krumme et al. 2009). This measure, of course, carries the problem to determine which shape would mean more or less herding, a likely error prone step.

(4) Average time interval between two consecutive bids (Luo and Lin). Although this measure is probably the easiest to calculate, it is in our opinion also inferior to measuring herding because it is a function of loan amount of number of bids received.

For this paper, we choose option one and focus on Zhang and Liu's regression model to measure herding (please see table 4 in model 2 in: Zhang and Liu (2012) for a thorough explanation). We choose this model because of its rigor. For each listing, the dependent and independent variables are extracted for each day of the auction. All data points are grouped by day and the independent variables are regressed on the dependent variable. The coefficient of LagTotalAmount for each day serves as our herding measure.

Variable Type	**Variable**	**Description**
Dependent Variable		
	AmountFunded	Amount of funding received during the day of auction *t*
Independent Variable		
Time varying listing attributes	LagTotalAmount	**Herding measure.** Sum of amount of fund received until previous day *t-1*
	LagPercentNeeded (%)	Percentage of funding still needed at day *t-1*
	LagTotalBids (Excluded after multicollinearity problems)	Sum of number of bids received until day *t-1*
	LagTotalAmountXLagPercentNeeded	Interaction term to account for payoff externalities.
Time invariant listing attributes	AmountRequested (1,000)	The amount requested in the listing.
	MaxBorrowerRate (%)	The interest rate the borrower offers at the start of the listing.
	Credit grade or prosper rating (Dummy variables (Y=1) for each category)	The credit grade or internal prosper rating of the listing based on the credit history and/or internal Prosper factors (: 'AA' (best rating), 'A', 'B', 'C', 'D', 'E', 'HR' (worst rating)'). The credit grade was replaced by the prosper rating.
	DebtToIncome	The debt to income ratio of the borrower.
	Homeowner (Y=1)	Whether the borrower is a homeowner.
	Groupmember (Y=1)	Whether the borrower belongs to a group.
	AuctionDay	Day into a listing's duration.

Table 2: Herding Model

We deviate from Zhang's model in the following: We leave out endorsements because Prosper's archival data only give a snapshot of endorsements as they are at the time of the download. Changes (such as removed endorsements) do not show up and values might not be entirely accurate. Based on previous studies, we also don't expect endorsements to have a major effect as economic variables are more important in predicting our lenders make their lending decisions (see e.g., (Greiner et al. 2010)). We leave out borrower rate at the end of each day (Lag Rate) because it highly correlates with MaxBorrowerRate which is the starting interest rate. Instead of a binary high risk variable that would identify listings with a credit grade of 'HR' (high risk), we include all credit grade or prosper rating categories. Credit grade and prosper rating have a high influence of the choice of a listing based on previous studies (Berger et al. 2009; Greiner et al. 2010; Kumar 2007) and only identifying one category might not be enough to adequately include this effect. After we run the first analyses, we had to remove LagTotalBids (number of bids received until day *t-1*) because of multicollinearity issues with LagTotalAmount (r=.89) for all daily regression values (VIF factors of +20). After removing LagTotalBids the VIF returned to values below 10 (around 2 to 3).

Sample 1 Description

We use public available data from Prosper from 2/15/2006 to 5/31/2012. Prosper went through a quiet period (all operations were paused) due to SEC regulations between 10/15/2008 and 7/13/2009, so no data is available for these days. We left out the first day of every listing. Including the first day doesn't make sense, because – taking the day as the unit of analysis – per definition there cannot be herding on the first day. This has also the advantage that listings that closed during the first auction day are automatically excluded from the analysis. Listings can close for several reasons before the auction ends. First, the borrower decided to cancel or withdraw the listing at any time. Second, if the listing is fully funded, the borrowers can decide to close the listing although the auction has not yet ended. However, until the borrower closes the listing, lenders do not know whether a listing closes, that's why we include all listings irrespective of the final status ('Completed' (loan fully funded), 'Expired' (not fully funded), 'Withdrawn', and 'Cancelled').

Calculating the Herding Measure

In a next step, we divided the data into each auction day and run the regression model for each day. From these results, we extracted the variable: LagTotalAmount which gives us the extent of herding on that particular auction day. This resulted in a time series containing a measure of herding. The following figure shows the herding measure over time.

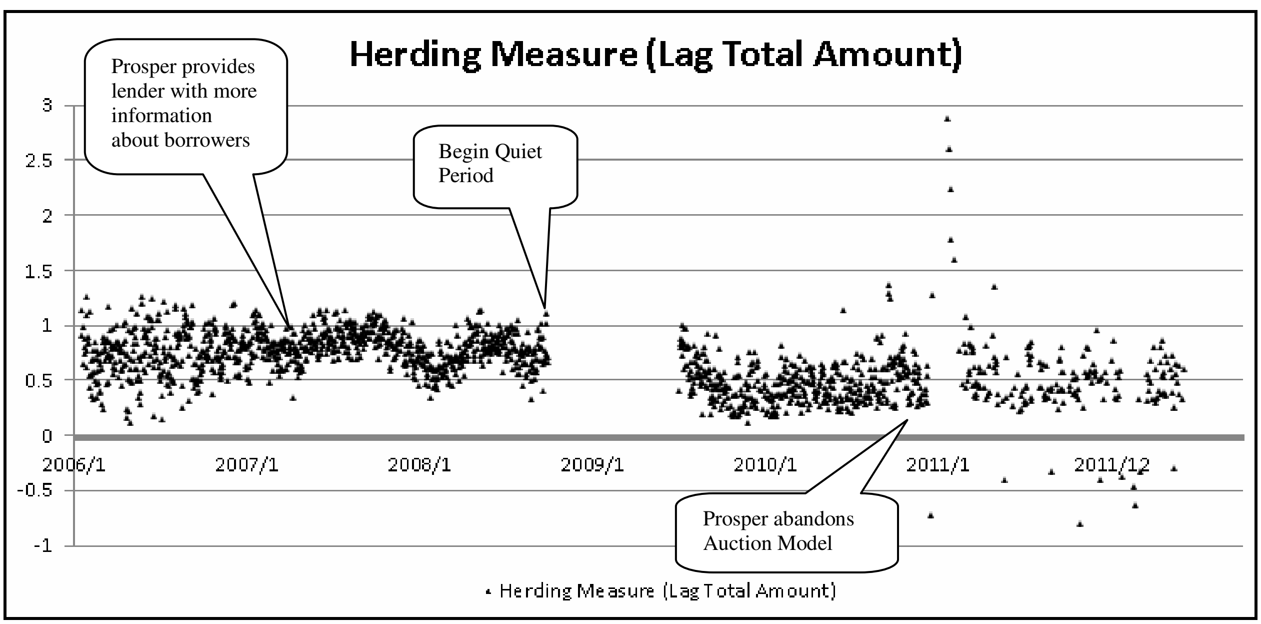


Figure 1: Herding Measure over Time

Per visual evaluation, we can distinguish between four separate time periods. (1) First, a period where the herding measure seems to fluctuate around the same level with a wide dispersion of values (2006/2 – 2007/3). (2) Then, a second period where the herding measure displays less dispersion, but with levels going up and down (2007/4-2008/10). We can only guess why the herding measure is more consistent in this period. In February 2007, lenders got access to more information about the borrower including extensive credit data Q&A in listings. These changes could have caused the measure to behave more consistently, but lenders might have also learned more about the lending process. It might be a combination of both, since Prosper frequently adjusted their business model and added new features within the first years. (3) After the quiet period, the herding measure decreases and stays on a lower level than before the quiet period (2009/7-2010/11). Prosper abandoned its auction model in December 2010 and switched to a set-price model where interest rates are pre-determined and a listing closes as soon as necessary funding is reached. This does not allow lenders to bid down the interest rate anymore. The herding model does not seem to work with this new set-price model. Dispersion of the measure is very high and the majority of the herding measures (coefficient of LagTotalAmount) are not significant at a p<.05 value anymore. And this makes sense if we look at when listing closed before and after the auction model change (see next figure).

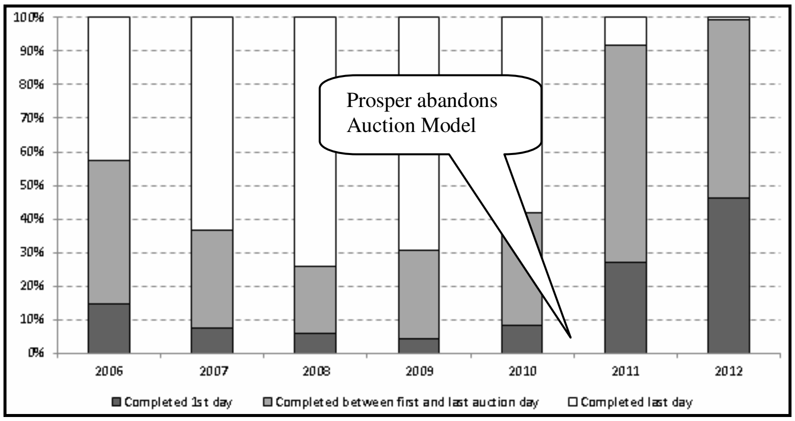


Figure 2: Listings successfully completed on 1st, middle, or last auction day (%)

During the auction model, most listing closed at the last day which means that lenders were able to bid on the listing over the whole duration of the auction duration (mostly durations of 7 or 10 days). With the fixed price model many listings close as early as within the first day and barely a listing will close during the last auction day. This means that a daily herding measure is not adequate, and another measure needs to be constructed (e.g., on an hourly base or taking a completely other measure). In the following, we leave out the fourth period and concentrate on the period between 2/15/2006 until 11/30/2010. The next figure shows the herding measure together with a 14 day moving average.

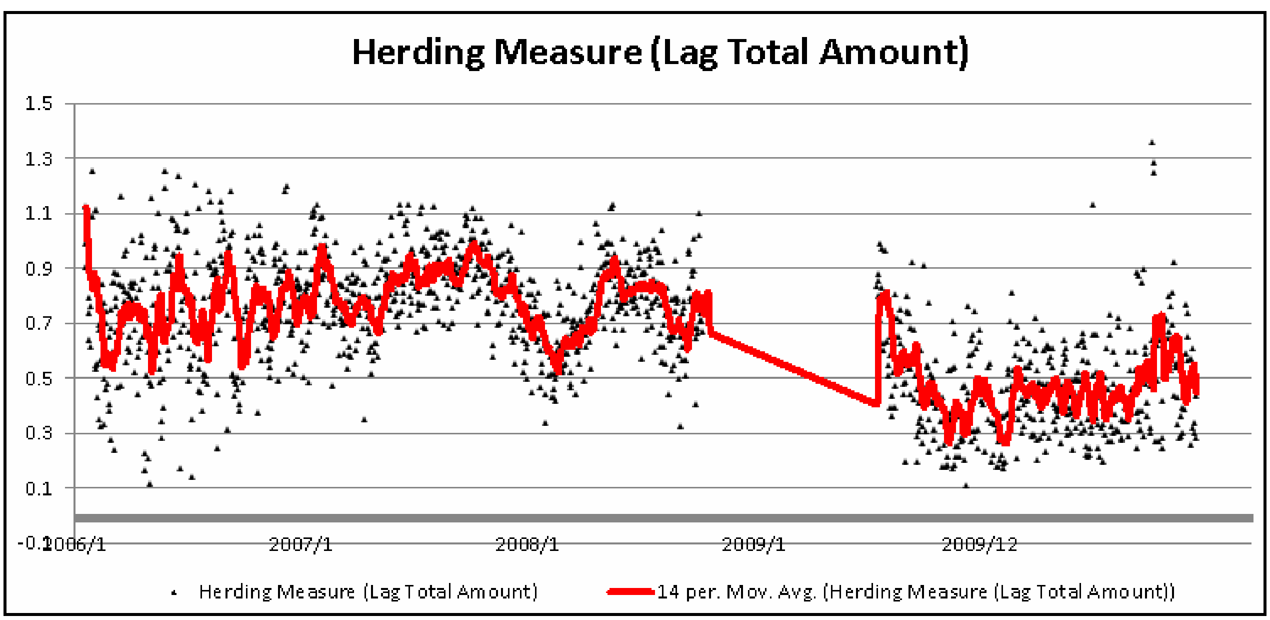


Figure 3: Herding Measure

The final sample we used to calculate the herding measure contains 1,636,617 auction days extracted from 289,927 unique listings with statuses Expired (187,920), Withdrawn (65,463), Complete (30,533), and Cancelled (6,011). The following two figures present descriptive of the sample.

	N	Minimum	Maximum	Mean	Std. Deviation
AmountFunded (Dependent Variable)	1636617	.0000000000	125360.0000000000	269.771772736073	1359.3779531371600
LagTotalAmount	1636617	.0000000000	598940.7500000000	784.113039226644	3123.0966376074500
LagPercentNeeded (%)	1636617	-31423.1973684211	100.0000000000	88.219946625330	45.3870715302373
LagTotalAmountXLagPercentNeeded	1636617	-18820633399.24	625000.00	-25988.2053	14719730.48751
AmountRequested (1,000)	1636617	1.0000000	25.0000000	7.349313623	6.2309698996
MaxBorrowerRate (%)	1636617	0	50	19.91	8.945
HR	1636617	0	1	.45	.497
E	1636617	0	1	.17	.376
D	1636617	0	1	.15	.357
C	1636617	0	1	.10	.300
B	1636617	0	1	.05	.227
A	1636617	0	1	.04	.201
AA	1636617	0	1	.03	.180
DebtToIncome	1636617	0	1001	48.26	123.966
Homeowner (Y=1)	1636617	0	1	.35	.477
Groupmember (Y=1)	1636617	0	1	.28	.450
AuctionDay	1636617	2	14	4.84	2.288
Valid N (listwise)	1636617				

Figure 4: Descriptive Statistics of Sample

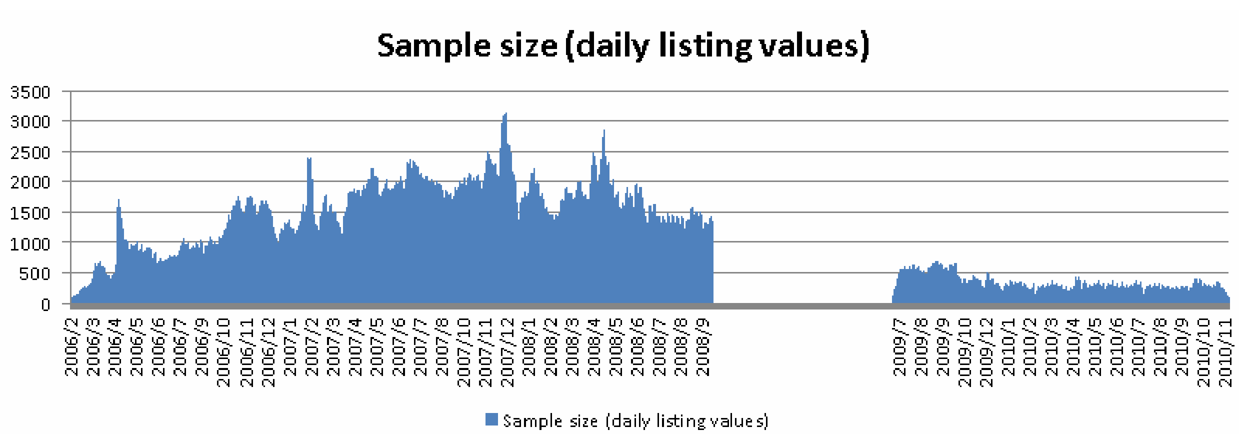


Figure 5: Sample Size per Auctionday

Sample 2: Extracting Determinants

Once we calculated the herding measure for every day, we extracted relevant daily variables from Prosper's archival data and other economic sources that we will use as independent variables in order to test our hypotheses.

Independent Variable	Description
Active listings	Listings that are active on the auction day.
Active lenders on Auction day	Unique lenders that bid during the auction day
Active lenders Average Experience	The average experience measured in number of bids of unique active lenders
Percentage high risk listings	The percentage of high risk listings of all active listings on the auction day
CPI-U	Consumer Price Index – Urban
Unemployment Rate	Unemployment Rate
Vix	Volatility Index
LnSP500Delta	Natural log of SP500 change from previous auction day
Average Bidden down from Starting Interest Rate	How much lenders bid down listings that are active on the auction day and completed successfully (MaxBorrowerRate – Borrowerrate)
Percentage completed (separated in High Risk, Middle Risk, Low Risk)	How many of the active listings on the auction day completed successfully.
Average Interest Rate (separated in High Risk, Middle Risk, Low Risk)	Average interest rate of the active listings on the auction day that completed successfully

Table 3: Variables for Sample 2

The following table gives descriptive of this second sample. The unit of analysis is an auction day.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Herding Measure	1424	.1066	1.3566	.679834	.2304560
Active listings	1499	5	4603	1702.75	1074.763
Active lenders on Auction day	1749	0	4477	1458.80	1166.913
Active lenders average experience	1749	0	740	248.18	167.340
Percentage high risk listings	1499	21.7391	83.2763	58.906091	11.5524638
CPI-U	1749	198.70	219.96	211.5768	6.10555
Unemployment Rate	1749	4.1000	10.6000	6.777644	2.2722779
Vix	1749	9.8900	80.8600	23.793282	12.0441187
LnSP500Delta	1749	-.0947	.1096	-.000050	.0133001
Average Bidden down from Starting Interest Rate	1475	.0000	16.5500	2.234595	1.5326472
Percentage completed high risk listings	1448	.0927	100.0000	14.284519	23.6465667
Percentage completed middle risk listings	1432	1.6393	100.0000	36.314658	23.9823827
Percentage completed low risk listings	1391	4.5455	100.0000	56.161635	22.5479837
Average interest rate high risk listings	1365	11.0000	49.7500	27.826944	4.6089987
Average interest rate middle risk listings	1432	8.8750	34.5000	19.402571	3.1206496
Average interest rate low risk listings	1391	5.7000	18.5700	10.428798	1.6989193
Valid N (listwise)	1249				

Figure 6: Statistics of Sample 2

RESULTS

In the following we show the preliminary results of our data analysis. These results should be taken with a grain of salt, since working with time series is a difficult task. We decided to show the scatterplots as well as simple regressions to give a first idea of how the results might look like.

Internal Determinants of Herding (Testing Hypotheses H1-H4)

The first step to investigate the internal determinants of herding was to look at the scatter plot charts of all four variables: active listings, active lenders, lender experience (in number of bids), and the percentage of high risk listings. The following table shows the scatter plots in the second row, and the variable over time in row three including a 14 day moving average (the flat line part in the middle represents the quiet period).

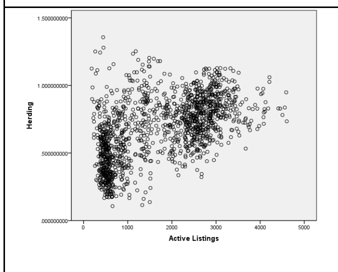
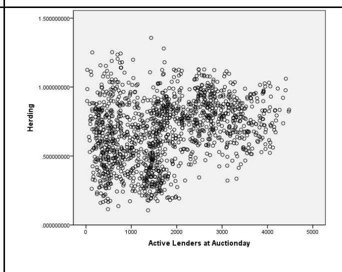
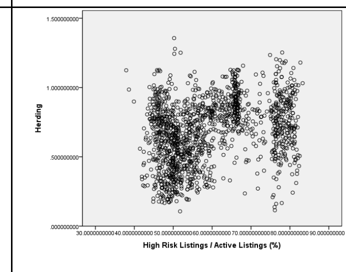
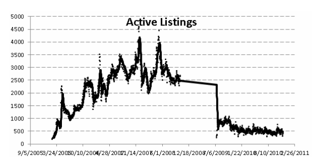
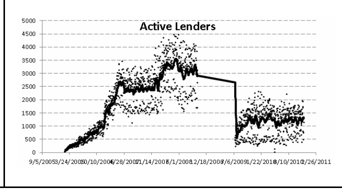
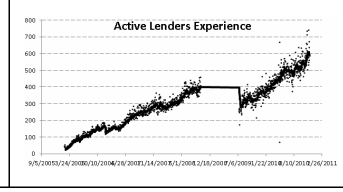
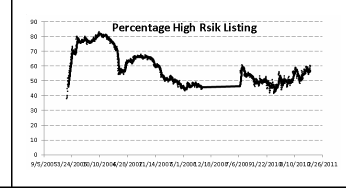
Active Listings	Active Lenders	Active Lender Experience	Percentage High Risk Listings
			
			

Table 4: Internal Determinants of Herding

The scatterplots give some first indication of a relationship between the determinants (x-axis) and the herding measure (y-axis). We also run simple multiple regression on the internal determinants of herding to get a better idea of the correlations. The next figure shows the results.

Active Listings	0.470 ***
	(.000)
Active Lenders	0.011 n.s.
	(.000)
Active Lender Experience	-0.193 ***
	(.000)
Percentage High Risk Listings	0.124 ***
	(.001)
Adjusted R-squared	0.375
No. observations	1423

Figure 7: Regression Results Internal Determinants

The results are interesting. As predicted, the number of listings is positively correlated with herding supporting hypothesis H1. The number of active lenders on the day is not significant (no support for hypothesis H2); however, the average experience of active lenders is negatively correlated with herding supporting hypothesis H3. This could mean that not the number of active lenders matter, but how experienced they are. This result, however, should be taken with a grain of salt, since the experience of lenders steadily increased. Since herding was very low after the quiet period, this negative effect could be the result of a natural increasing experience of active lenders and the low level of herding. As predicted, the higher the percentage of high risk active listings, the bigger the herding measure supporting hypothesis 4.

External Determinants of Herding (Testing Hypothesis H5)

We measure the economic climate with the following basic economic indicators:

(1) Consumer Price Index (CPI-U) measures inflation in an economy and reflects uncertainty

(2) Unemployment rate reflects uncertainty in an economy

(3) Volatility index of the Sp500 (Vix) reflects volatility and angst

(4) Natural logarithm of SP500 change ($SP500_t$ / $SP500_{t-1}$) reflects positive or negative climate

The following table shows the scatter plots and the measures over time.

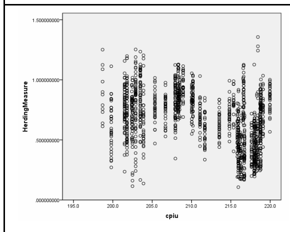
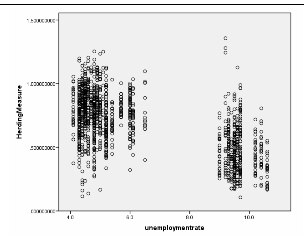
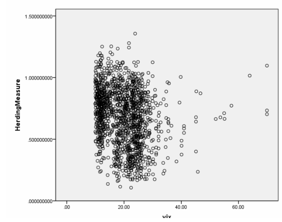
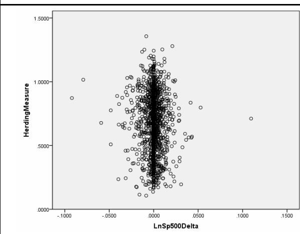
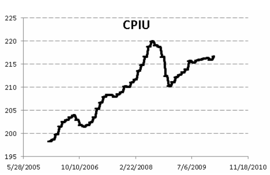
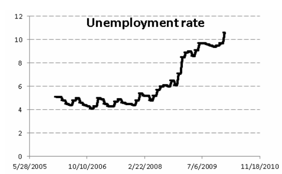
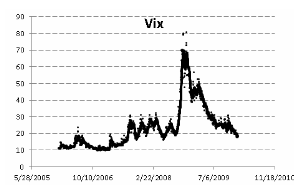
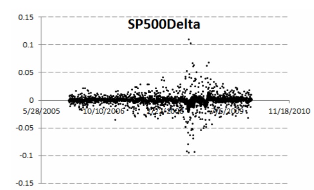
CPI-U	Unemployment Rate	Vix	Ln(SP500Delta)
			
			

Table 5: External Factors

We also performed multiple regression on the herding measure. The following figure shows the results.

Consumer Price Index - Urban	0.173 ***
	(.001)
Unemployment Rate	-0.731 ***
	(.003)
Vix	0.014 n.s.
	(.001)
Ln(SP500Delta)	0.040 n.s.
	(.471)
Adjusted R-squared	0.384
No. observations	1423

Standard errors are reported in parentheses

**** P<.001, ** p<.01, *p<.05, n.s. p>.05*

Dependent Variable: Herding Measure

Figure 8: Regression Results External Factors

The results show that only the inflation rate (CPI-U) is positively related to herding. This would suggest that in an environment with higher inflation and resulting uncertainty herding is higher. The unemployment rate is significant, however, goes the opposite direction as predicted. The volatility index (Vix) and SP500 change are not significant. For now, we determine that support for our hypothesis H5 is not conclusive.

Consequences of Herding (Testing hypotheses H6-H8)

For the consequences of herding, we looked at seven different variables. For H7 and H8, we divide the measure into three separate measures reflecting credit grade of borrowers (High Risk = 'HR', 'E'; Middle Risk = 'D', 'C', 'B'; Low Risk = 'A', 'AA'). Our question is whether herding has the potential to influence the outcome of the lending process. The following table shows the scatter plot for each of the variables (Y-axis) and the herding measure (X-axis).

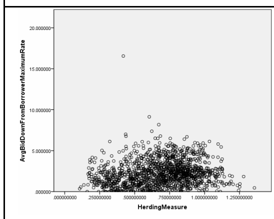
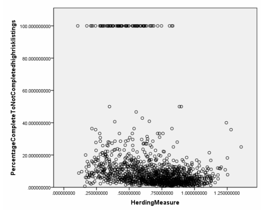
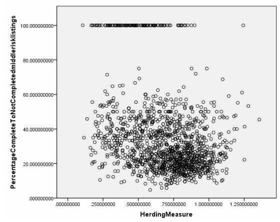
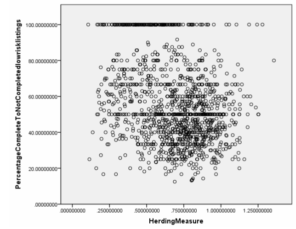
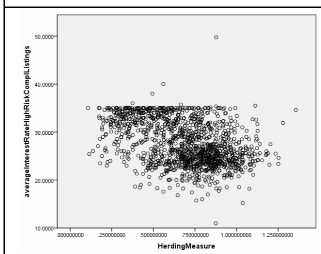
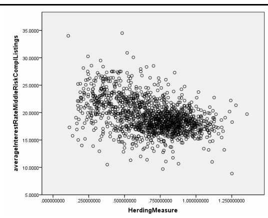
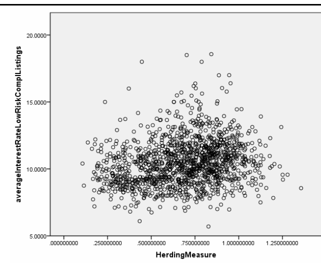
Average Bidden down from Starting Interest Rate	Percentage completed High Risk	Percentage completed Middle Risk	Percentage Completed Low risk
			
Average Interest Rate High Risk	Average Interest Rate Middle Risk	Average Interest Rate Low Risk	
			

Table 6: Consequences of Herding

We also performed several regression analyses with the single independent variable herding measure. The results are shown in the next table.

Dependent Variable	Coefficient of Herding Measure	Adj. R-Square	Model Fit
Interest Rate Bidden Down	.170 (.000)	2.80%	42.265 (.000)
Successfully completed listings / Completed + Expired Listings (in %, High Risk Listings only)	-.313 (.000)	9.70%	150.860(.000)
Successfully completed listings / Completed + Expired Listings (in %, Middle Risk Listings only)	-.326 (.000)	10.60%	163.196 (.000)
Successfully completed listings / Completed + Expired Listings (in %, Low Risk Listings only)	-.273 (.000)	7.40%	107.437 (.000)
Average Interest Rate of Completed High Risk Listings	-.405 (.000)	16.30%	258.163 (.000)
Average Interest Rate of Completed Middle Risk Listings	-.432 (.000)	18.60%	315.016 (.000)
Average Interest Rate of Completed Low Risk Listings	.205 (.000)	4.10%	59.564 (.0000

Table 7: Consequences of Herding (IV = Herding Measure)

Interpreting the scatter plot and regression analyses for the consequences of herding is the most difficult one. The scatter plots don't show definite trends in most variables and the regression analyses would need to be expanded by other independent variables that also influence the dependent variable. As they are now, we assume that the coefficients are inflated. Still, interestingly the trend (+/-) go the direction as stated in our hypotheses with the exception of the average interest rate for low risk listings. It seems that not all types of listings equally profit from herding.

CONCLUSION AND SUMMARY OF RESULTS

Summary

The following table provides an overview of our hypotheses and whether they were supported or not.

Hypothesis	Tentative Result
H1: The number of active listings positively influences herding.	Supported.
H2: The number of active lenders positively influences herding.	Not Supported.
H3: The experience of lenders negatively influences herding.	Supported.
H4: The percentage of high risk active listings positively influences herding.	Supported.
H5: A high volatile, uncertain, and negative economic climate positively influences herding.	Inconclusive.
H6: Herding positively influences bidding down the interest rate.	Supported.
H7: Herding negatively influences the percentage of listings that are completed.	Supported.
H8: Herding negatively influences the average interest rate.	Inconclusive.

Table 8: Summary of Results

Future Research

Since this is the first attempt to understand the determinants of herding, there are many possibilities for future research. Future research could look at other consequences of herding such as loan performance and lender return. Interaction effects (e.g., SP500 and Vix) or non-linear relationships of factors should be investigated. Future research should also investigate herding in the excluded period after Prosper changed to a fixed-price model. For this paper, we choose Zhang's et al. model. Future research could investigate alternative herding measures (e.g., Herzenstein et al. (2011)).

Limitations

Our research is limited by the data available from Prosper.com. There might be factors influencing herding that cannot be easily measured. Another limitation is that Prosper changed his business model several times over the years (e.g., see group discussion in (Wang et al. 2011)). This means not all measures might be available for all periods, and calculation of measures might change (e.g., credit grade, prosper rating). However, we don't think that this poses a problem for our research. The herding measure is calculated on a daily base and we only assume that our model and measures hold true on this day. Since we do not attempt to interpret coefficients other than the herding measure (LagTotalAmount) changes of measures should not affect our herding measure.

Conclusion

We presented a model to measure herding in P2P lending marketplaces. Based on different proposed measures, we selected one herding measure and empirically calculated a time series for the first 4 years of Prosper's marketplace. Then, we looked at internal and external factors likely to influence the level of herding. Our preliminary analysis shows that there is support for the internal factors, but not conclusive support for external factors influencing herding. We also examined consequences of herding and found that borrowers, on the one hand, can benefit from herding by lower interest rates, on the other hand, less listings get completed because lenders concentrate their bidding activity on fewer listings when herding is high. There is also indication that not all borrowers are equally affected by herding behavior.

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